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Climate change impact under alternate realizations of climate scenarios on maize yield and biomass in Ghana

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ABSTRACT

Climate change is unequivocal and these changes have increased over the past few years. The recent vulnerability and prospect of climate variability and change impact, thus, warrants measures now to reduce the adverse impacts. This study presents an estimate of the effects of climate variables on potential maize productivity and an assessment of the most limiting climatic drivers in the future climate scenarios for maize production in central Ghana, constituting major maize production areas. The time-slices 2000, 2030 and 2080 were chosen to represent the baseline, near future and end century climate, respectively. Furthermore, two Representative Concentration Pathways (RCP_s) namely RCP 4.5 and RCP 8.5 from the GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES, General Circulation Models (GCMs), were selected. Simulations based on the model LINTUL5 were used to estimate the crop responses.

There is an average increase in the maize yield and aboveground biomass in the projected scenarios by 57% and 59% respectively under HadGEM2-ES (RCP 8.5) in the time horizon 2030. However, variability in the projected average maize yield and above ground biomass compared to the baseline values, is ranging from 183.6 kg ha^{-1} under HadGEM2-ES (RCP 8.5) by time horizon 2080 to a maximum of 1326.8 kg ha^{-1} under HadGEM2-ES (RCP 8.5) by 2030 and a minimum increase of 169.9 kg ha^{-1} under GFDL-ESM2M (RCP 8.5) by time horizon 2080 to a maximum increase of 2386.1 kg ha^{-1} under HadGEM2-ES (RCP 8.5) by time horizon 2030.

The reasons for potential benefit in maize yields across the climate scenarios was attributed to the positive effect of CO_2, reduced water stress reflected by lower atmospheric water demand during crop growth period. It also indicates that water is the limiting factor for maize production in the study region. However, temperature (through shortening of the maize growing cycle), and solar radiation may remain the limiting factors for maize production.

1. Introduction

Africa as a whole is one of the most vulnerable continents in the face of climate change due to its high exposure and low adaptive capacity (Sultan and Gaetani, 2016; Niang et al., 2014). In the Sahel and savannah parts of Africa in particular, climate scientists have shown that extreme temperatures have increased, while precipitation has reduced over the last fifty years (Frimpong and Kerr, 2015; Seneviratne et al., 2012). In the coming decades, global climate change will have an impact on all sectors of the global economy. But most impacts will fall on the agricultural sector, creating food insecurity particularly in the developing world (Ringler, 2008; Nelson et al., 2009).

The impact assessment of future climate change in Ghana has received much attention due to increasing drought and flood events in the last four decades (Asante and Mensah, 2015; Tachie-Obeng et al., 2014). In Ghana, the agricultural sector is dominated by smallholder farmers who cultivate about 1–2 ha of land and produce 80% of the country's agricultural output. In spite of the importance of the agricultural sector, it is the most vulnerable sector, when issues of climate change are discussed since the sector mostly depends on rainfall to undertake its activities (Asante and Mensah, 2015). According to the General circulation model (GCM) HadGEM2-ES (RCP 8.5) prediction, there would be a reduced precipitation by − 32.1 mm and increased mean temperature in the tune of 11.7 °C as per HadGEM2-ES (RCP 4.5) in the central Ghana region by the time horizon 2080 compared to baseline 2000. Given the fact that West Africa constitutes about 27% of the population of Africa and 16% of its population is undernourished,

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Table 1a
Projected carbon dioxide (CO_2) concentration (in ppm) used in the study for different climate scenarios and time periods.

Climate scenarios	CO2 concentration (in ppm)
Baseline	369
GFDL-ESM2M (RCP 4.5 - 2030)	450
GFDL-ESM2M (RCP 4.5 - 2080)	575
GFDL-ESM2M (RCP 8.5 - 2030)	475
GFDL-ESM2M (RCP 8.5 - 2080)	950
GISS-E2-H (RCP 4.5 - 2030)	450
GISS-E2-H (RCP 4.5 - 2080)	575
GISS-E2-H (RCP 8.5 - 2030)	475
GISS-E2-H (RCP 8.5 - 2080)	950
HadGEM2-ES (RCP 4.5 - 2030)	450
HadGEM2-ES (RCP 4.5 - 2080)	575
HadGEM2-ES (RCP 8.5 - 2030)	475
HadGEM2-ES (RCP 8.5 - 2080)	950

Table 1b
Correction of radiation use efficiency as a function of atmospheric carbon dioxide (CO_2) concentration (in ppm) used in the crop model.

CO_2 concentration (in ppm)	Correction factor
40	0
360	1
720	1.1
1000	1.1

the impacts of global climatic changes could particularly exacerbate the already poor performance in food production being experienced in this region. In relation to Ghana, the cropping systems are highly varied and this reflects the dynamic adaptations to increasing population pressure, land insecurity, climate variability, and new trading opportunities or markets (Stanturf et al., 2011) and hence, ability to meet the future demands may hinge upon proper assessment of medium-and long-term maize production vulnerability to climate change and the measures taken to adapt accordingly. Maize can grow at higher temperatures compared to many other cereal crops and therefore be a suitable crop for warmer conditions. Maize is well adapted to well-drained soils (Landon, 1991) but sensitive to water stress (Doorenbos and Kassam, 1979). Thus, maize productivity under future climates depends to a large extent on the future rainfall conditions in the central Ghana (Tachie-Obeng et al., 2014). However, Srivastava et al. (2017) have pointed out that in the central Ghana, radiation and temperature are the limiting factors for observed as well as simulated actual maize productivity.

One source of uncertainty regarding the impact of climate change is uncertainty about the most appropriate choice of climate model and greenhouse gas emissions scenario. It is assumed that climate change will fall within the range of future conditions predicted by different climate models (Araya et al., 2015; Asseng et al., 2013; Challinor et al., 2013). Impact assessments on crop production, therefore, must be based on multi-model climate projections, which are assumed to provide a more representative range of climate change impacts than single-model approaches (Tao et al., 2009; Taylor et al., 2009).

Crop models are useful tools for exploring the impact of climate and management scenarios on agricultural response indicators such as crop yield (Ruane et al., 2013; Rosenzweig et al., 2013). Detailed climate change impact assessment studies on maize are scarce for central Ghana, constituting a major maize production area in the country. Better knowledge of how climate will change in central Ghana and how such changes will impact crop productivity is crucial to inform policies that may counteract the adverse effects. In this backdrop, the objective

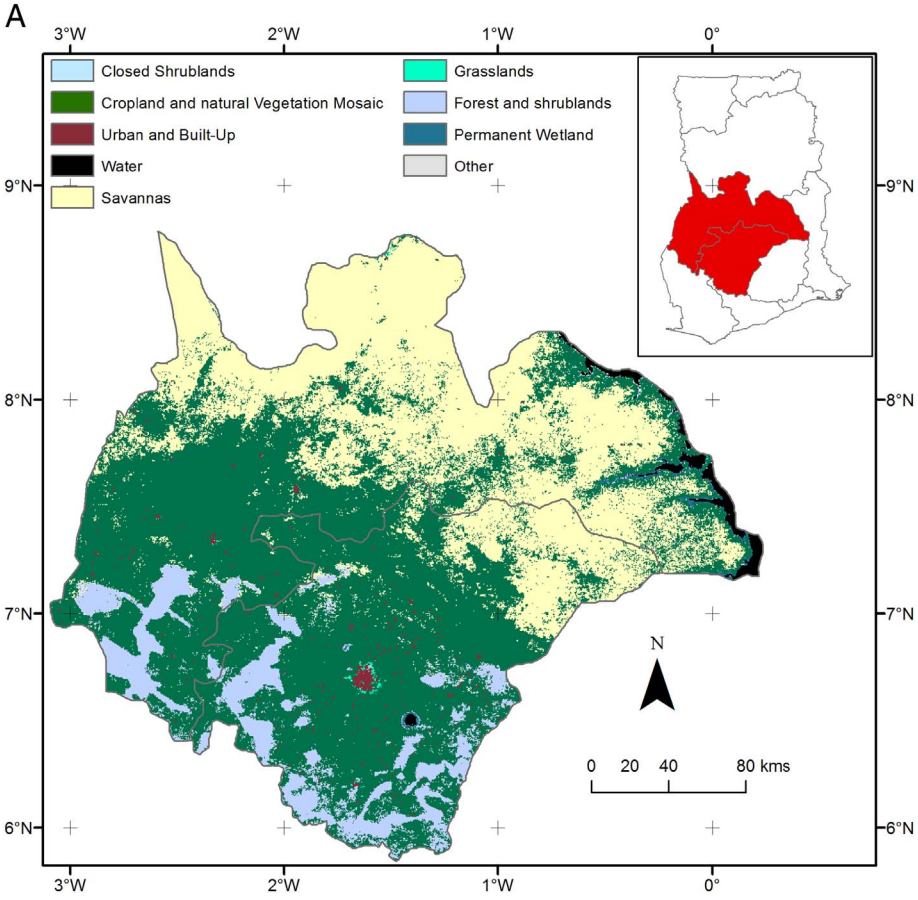

Fig. 1a. Land use map of Central Ghana covering the study region.

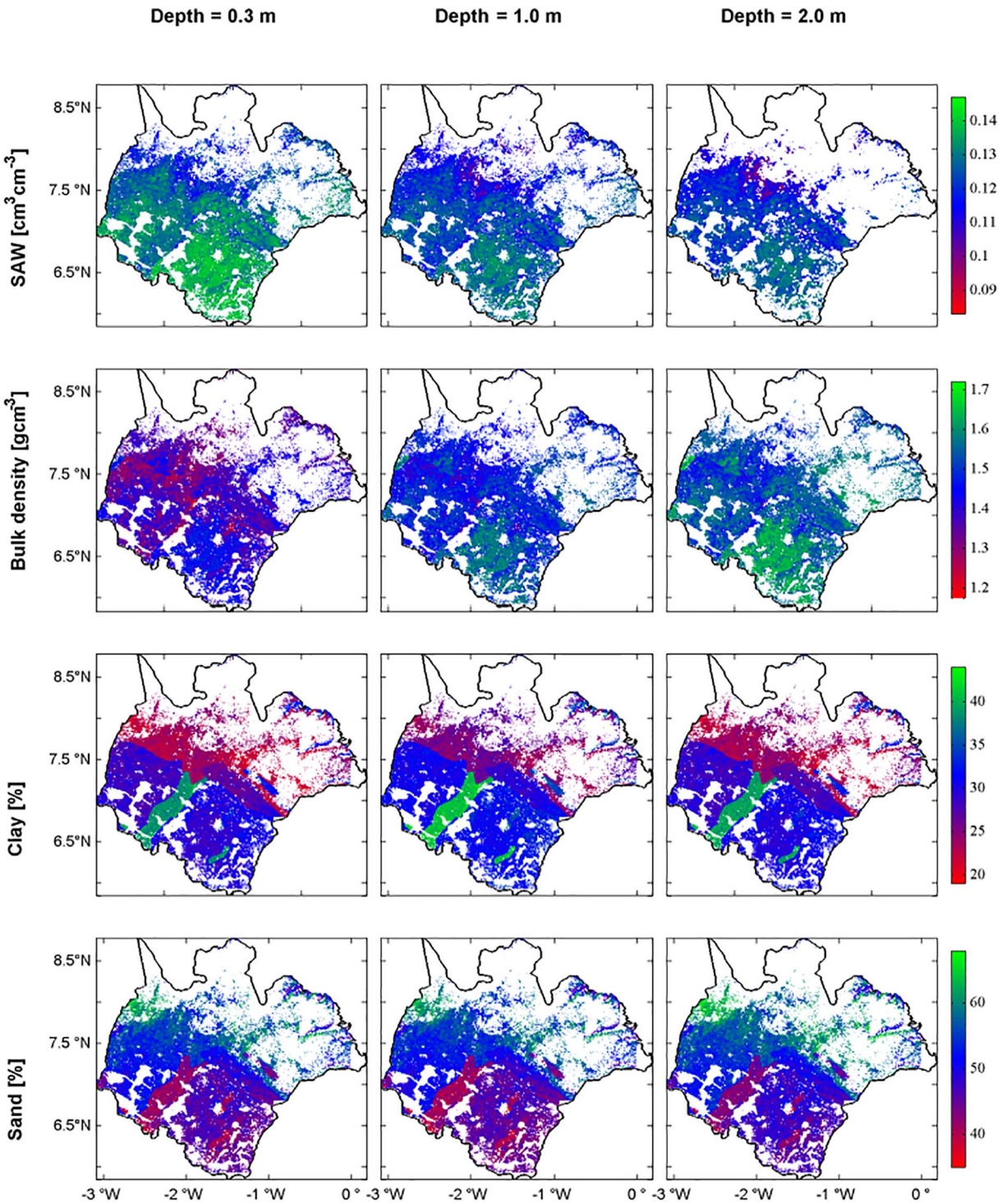

Fig. 1b. Soil physical properties (sand, clay, bulk density and soil available water (SAW) at three soil depths (i.e., 0.3, 1.0 and 2.0 m)) of Central Ghana covering the study region.

of this study was to (1) perform an impact assessment of climate change scenarios on potential productivity of maize using crop model simulations based on three General Circulation Models (GCMs), two Representative Concentration Pathways (RCP_s) for two time horizons 2030s and 2080s, near future and end century respectively in central Ghana and (2) assess the future most limiting climatic drivers for maize production in the central Ghana.

2. Materials and methods

2.1. Description of study region

This study was carried out in the Ashanti and Brong-Ahafo regions in of the central Ghana. The Ashanti Region is an administrative region lies between longitudes 0.15 W and 2.25 W, and latitudes 5.50 N and 7.46 N and occupies a total land surface area of 24,389 km^2. The region has an average annual rainfall of 1270 mm and two rainy seasons. The major rainy season starts in March, with a major peak in May. There is a slight dip in July and a peak in August, tapering off in November.

Table 2
Crop parameters of LINTUL5 used in the study for long cycle variety 'Obatanpa' (same as Srivastava et al., 2016).

Name	Description	Unit	Value
Crop parameters			
TSUM1	Temperature sum from emergence to anthesis	°C day^{-1}	1060
TSUM2	Temperature sum from anthesis to maturity	°C day^{-1}	990
TBASEM	Lower threshold temperature for emergence	°C	8.0
TEFFMX	Maximum effective temperature for emergence	°C	30.0
TSUMEM	Temperature sum from sowing to emergence	°C	56.0
RUE-0.0	Radiation use efficiency at development stage 0	g MJ^{-1}	3.8
RUE-1.25	Radiation use efficiency at development stage 1.25	g MJ^{-1}	3.8
RUE-1.50	Radiation use efficiency at development stage 1.50	g MJ^{-1}	3.0
RUE-1.75	Radiation use efficiency at development stage 1.75	g MJ^{-1}	2.0
RUE-2.0	Radiation use efficiency at development stage 2.0	g MJ^{-1}	1.4
SLATB-0.0	Specific leaf area at development stage 0	m2 g^{-1}	0.022
SLATB-0.9	Specific leaf area at development stage 0.9	m2 g^{-1}	0.03
SLATB-1.0	Specific leaf area at development stage 1.0	m2 g^{-1}	0.032
SLATB-2.0	Specific leaf area at development stage 2.0	m2 g^{-1}	0.02
LAI critical	Critical leaf area beyond which leaves die due to self shading	m2 m^{-2}	4
RGRLAI	Maximum relative increase in LAI	ha ha^{-1} day^{-1}	0.02
ROOTDI	Initial rooting depth	m	0.1
ROOTDM	Maximum rooting depth	m	1
RRDMAX	Maximum rate of increase in rooting depth	m	0.012
TDWI	Initial total crop dry weight	kg ha^{-1}	5

December to February is dry, hot, and dusty. The average annual mean temperature is about 27 °C. Much of the region is situated between 150 and 300 m above sea level. The Brong-Ahafo region is also an administrative region in Ghana centred around between latitude 7.15°N and 8.45°N, occupying a total land surface of 39,557 km^2.The region has a tropical climate, with high temperatures averaging 23.9 °C and a double maxima rainfall pattern. Rainfall ranges, from an average of 1000 mm in the northern parts to 1400 mm in the southern parts.

2.2. Database description

Weather data is the driving force in crop simulation. To run simulations for projected climate change scenarios, weather data must match the requirements of crop models (Donatelli et al., 2015). A gridded data set was built; covering the Ashanti and Brong-Ahafo regions. In this study, the time-slices 2000 (centred over 1971–2000), 2030 (centred over 2016–2045) and 2080 (centred over 2064–2093) were chosen to represent the baseline and future climate, respectively. Future climate scenarios were compared to the reference time slice of 2000 (based on thirty years daily data of 1971–2000). Projections of future climate were obtained using CMIP5 and two Representative Concentration Pathways (RCP$_s$) for carbon emissions currently (IPCC, 2014). Future climate projections were created using the 'delta' method, in which the mean monthly changes for RCP$_s$ 4.5 and 8.5 for near future and end century time slices centred around 2030 and 2080, respectively, were applied to the daily baseline weather series. The future time scale weather series and the corresponding projected carbon dioxide (CO_2) concentration, according to RCP$_s$ 4.5 and 8.5 (Table 1a), were used in all crop model simulations (Wolf et al., 2012). The three GCMs used in this study are as follows:

i) GFDL-ESM2M: Geophysical Fluid Science Laboratory-Earth System Modelling developed by Princeton University, Princeton, NJ, USA.
ii) GISS-E2-H: Goddard Institute for Space Studies, developed by National Aeronautics and Space Administration (NASA), NY, USA.
iii) HadGEM2-ES: Hadley Centre Global Environment Model version 2, developed by Met Office Hadley Centre, UK.

The dataset published by Sheffield et al. (2005) was used as daily baseline weather time series from 1971 to 2000. The dataset had been constructed by combining a suite of global observation-based datasets with the National Centres for Environmental Prediction (NCEP)/National Centre for Atmospheric Research (NCAR) reanalysis. Known biases of the reanalysis in precipitation and near-surface meteorology have been shown to exert an erroneous effect on modelled land surface water and energy budgets and thus had been corrected using observation-based datasets of precipitation, air temperature, and radiation. Sheffield et al. (2005) also made corrections to the rain day statistics of the reanalysis precipitation which have been found to exhibit a spurious wave-like pattern in high-latitude wintertime. Wind-induced under catch of solid precipitation had been removed using the results from the World Meteorological Organization (WMO) Solid Precipitation Measurement Intercomparison. In this data, Precipitation is disaggregated in space to 1.0° by statistical downscaling using relationships developed with the Global Precipitation Climatology Project (GPCP) daily product. Other meteorological variables (downward short- and longwave, specific humidity, surface air pressure and wind speed) had been downscaled in space with an account for changes in elevation. The dataset was evaluated by Sheffield et al. (2005) against the bias-corrected forcing dataset of the second Global Soil Wetness Project (GSWP-2). The final product provides a long-term, globally- consistent dataset of near-surface meteorological variables that can be used to drive models of the terrestrial hydrologic and ecological processes for the study of seasonal and inter-annual variability and for the evaluation of coupled models and other land surface prediction schemes (Sheffield et al., 2005).

2.3. Crop growth model

The LINTUL5 (Wolf et al., 2012) model simulates potential crop growth limited by solar radiation, air temperature, and crop characteristics) under well-watered conditions, ample nutrient supply and the absence of pests, diseases, and weeds. Biomass production is based on intercepted radiation according to Lambert-Beer's law and light use efficiency. The produced biomass is partitioned among various crop organs (leaves, stems, storage organs and roots) according to partitioning coefficients defined as a function of the development stage of the crop. The phenology is simulated by the accumulation of thermal time above a defined base temperature. Photosynthesis and total crop growth rate are calculated by multiplying the intercepted light and radiation use efficiency (RUE). The length of crop growth cycle (i.e., total vegetation days of maize) in the model is defined by the number of days from emergence to the physiological maturity (Wolf et al., 2012). To simulate a continuous cropping system, the model was embedded

Table 3
Observed and simulated Aboveground biomass (AGB), Grain yield, Day of Anthesis (DOA), Day of Maturity (DOM), mean residual error (ME), and mean relative error (MR), N = number of replicates for the Obatanpa variety in the two sites of the administrative unit "Northern Region" of Ghana namely Akukayili and Cheshegu (latitude 9.15°N) (Srivastava et al., 2016).

Site		Treatment	N	DOA Observed	DOA Simulated	DOM Observed	DOM Simulated	Grain yield Observed (Mg ha^{-1})	Grain yield Simulated (Mg ha^{-1})	ME Grain yield (Mg ha^{-1})	MR Grain yield	AGB Observed (Mg ha^{-1})	AGB Simulated (Mg ha^{-1})	ME AGB (Mg h^{-1})	MR AGB
Obatanpa	Akukayili	Control	4	59	56	103	103	0.3	1.0	0.7	2.3	2.4	1.8	− 0.6	− 0.25
		Fertilized	4	56	56	103	103	2.6	3.5	0.9	0.3	6.7	6.4	− 0.3	− 0.04
	Cheshegu	Control	4	60	56	111	103	0.3	1.1	0.8	2.7	2.12	2.08	− 0.04	− 0.02
		Fertilized	4	56	56	111	103	2.7	3.3	0.6	0.2	6.7	6.2	− 0.42	− 0.06

into a general modelling framework, SIMPLACE (Scientific Impact Assessment and Modelling Platform for Advanced Crop and Ecosystem Management) (Gaiser et al., 2013). The SIMPLACE < LINTUL5-SLIM > solution of the modelling platform was used in this study. SLIM is a conceptual soil water balance model subdividing the soil in a variable number of layers, substituting the two layer approach in LINTUL5 (Addiscott and Whitmore, 1991). Water stress occurs when the daily available soil water is lower than the crop water demand calculated by Penman- Monteith FAO-56 approach (Allen et al., 1998). Water, nutrients (NPK), temperature, and radiation stresses restrict the daily accumulation of biomass, root growth, and yield. Stress indices are calculated daily. The stress index for water i.e., Water Stress Index (WSI, computed as ratio between actual and potential crop transpiration) and nutrient limitations i.e., Nutrient Stress Index (NSI, computed as a ratio between actual crop nutrient concentration and critical nutrient concentration, where critical nutrient concentration is the half of optimum nutrient concentration which depends on crop and development stage) range from 0.0 to 1.0. The value 0.0 indicates severe stress level and 1.0 indicates no stress. Water stress occurs when available water in the soil is below crop-water-demand. The same holds for nitrogen stress, that is when crop available nitrogen in the rooted soil profile is lower than crop nitrogen demand. The estimation of the daily increase in crop biomass, considers, on a given day, the maximum stress index among water, nitrogen, phosphorus and potassium stress. Crop water demand is estimated from the daily reference evapotranspiration and leaf area index according to Allen et al. (1998). The crop available water in a soil layer is reduced between a defined critical soil moisture threshold and wilting point and by root length density. The critical point is a crop specific value which is calculated according to Allen et al. (1998) and depends on crop development, soil water tension and potential transpiration. The model accounts for the effect of increasing atmospheric CO_2 concentration on radiation use efficiency (RUE). The model uses an interpolation table for correction of RUE as a function of atmospheric CO_2 concentration (Table 1b).

2.4. Model set-up for regional simulations

The actual simulation was done at the 1 km grid cell level, where cropland (Fig. 1a) and soil data are available (ISRIC soil database) for a total of almost 33,000 grid cells. The consequent level of abstraction of the production system was high enabling more detailed analysis of climate impacts at finer resolution. Values for relevant soil parameters (sand, silt, clay, cation exchange capacity, pH, organic carbon and bulk density) were extracted from the soil property maps of Africa at 1 km × 1 km resolution (http://www.isric.org/data/soil-property-maps-africa-1-km) (Fig. 1b). Other parameters such as soil water at field capacity, wilting point, saturation point and Van Genuchten parameters were computed (Rawls et al., 1993).

In this study long season maize cultivar "Obatanpa" (long cycle variety) related parameters (Table 2) were calibrated against the measurements collected from field trials in the administrative unit "Northern Region" of Ghana at a latitude of 9.15°N which is at the northern edge of the Brong-Ahafo Region.

A rule, based on rainfall (The first day of spell of 7 days in which at least 20 mm of rain falls, on condition that no dry period of more than 7 days occurs in the following 30 days) was used to estimate sowing date within the sowing window because rainfall based approaches are currently in use in Sub-Saharan Africa (Srivastava et al., 2016; Frimpong and Kerr, 2015; Laux et al., 2008; Dodd and Jolliffe, 2001; Diallo, 2001).

In the agro-climatic literature, this is referred to as the onset date of the Optimum Growing Period (OGP) (Laux et al., 2008). The OGP guarantees seed germination and survival after sowing. On the one hand, when sowing is carried out too early before the OGP, seeds are lost in the event of long dry spells. On the other hand, when sowing is carried out too late after the OGP, there is an abnormal growth of seeds

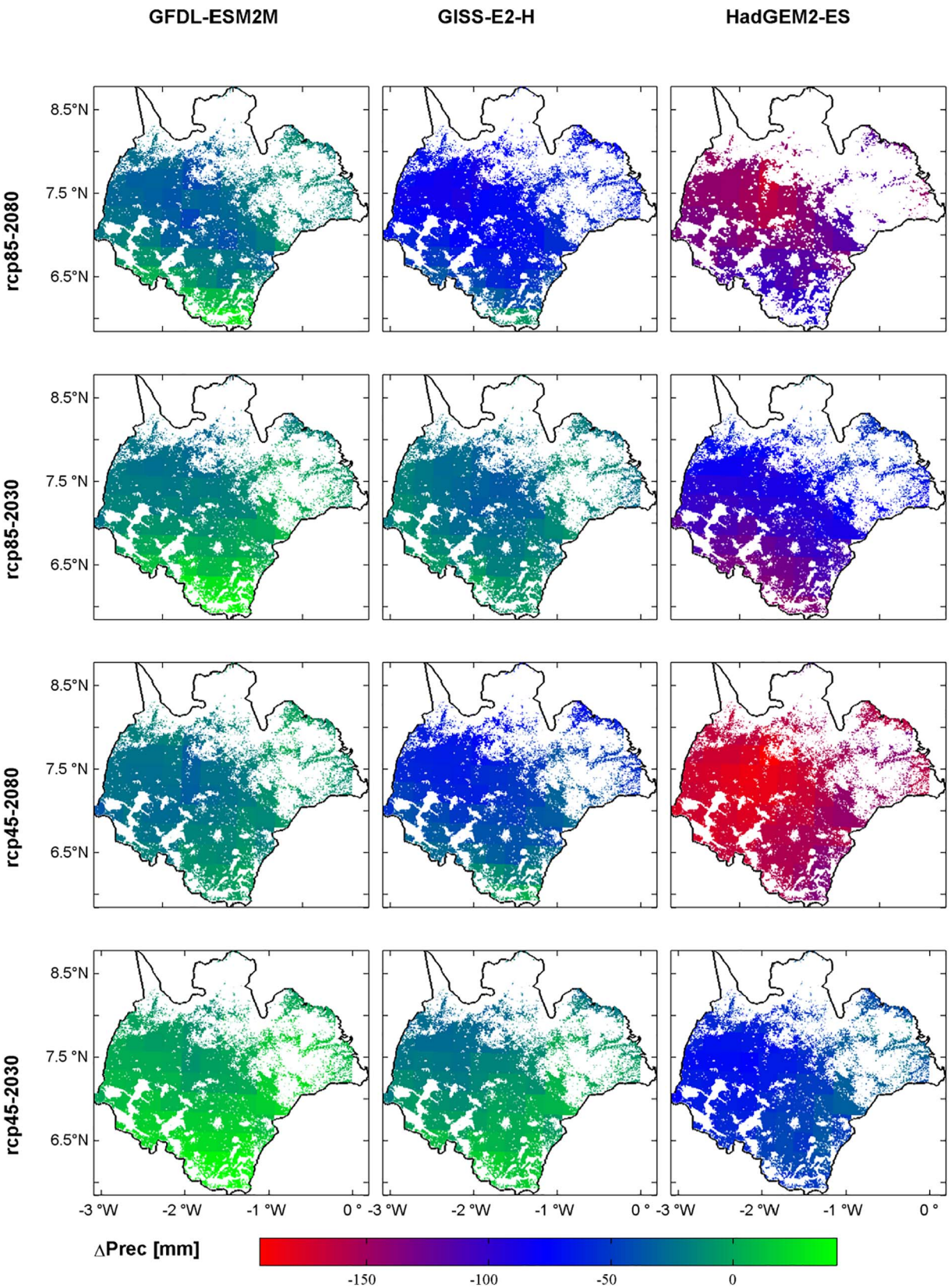

Fig. 2. Change in average cumulated precipitation (Prec) during the crop growth period for the RCP 4.5 and RCP 8.5 scenarios; time period: 2030–2000; 2080–2000 under the GCMs GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES compared to the baseline at columns 1, 2 and 3 respectively.

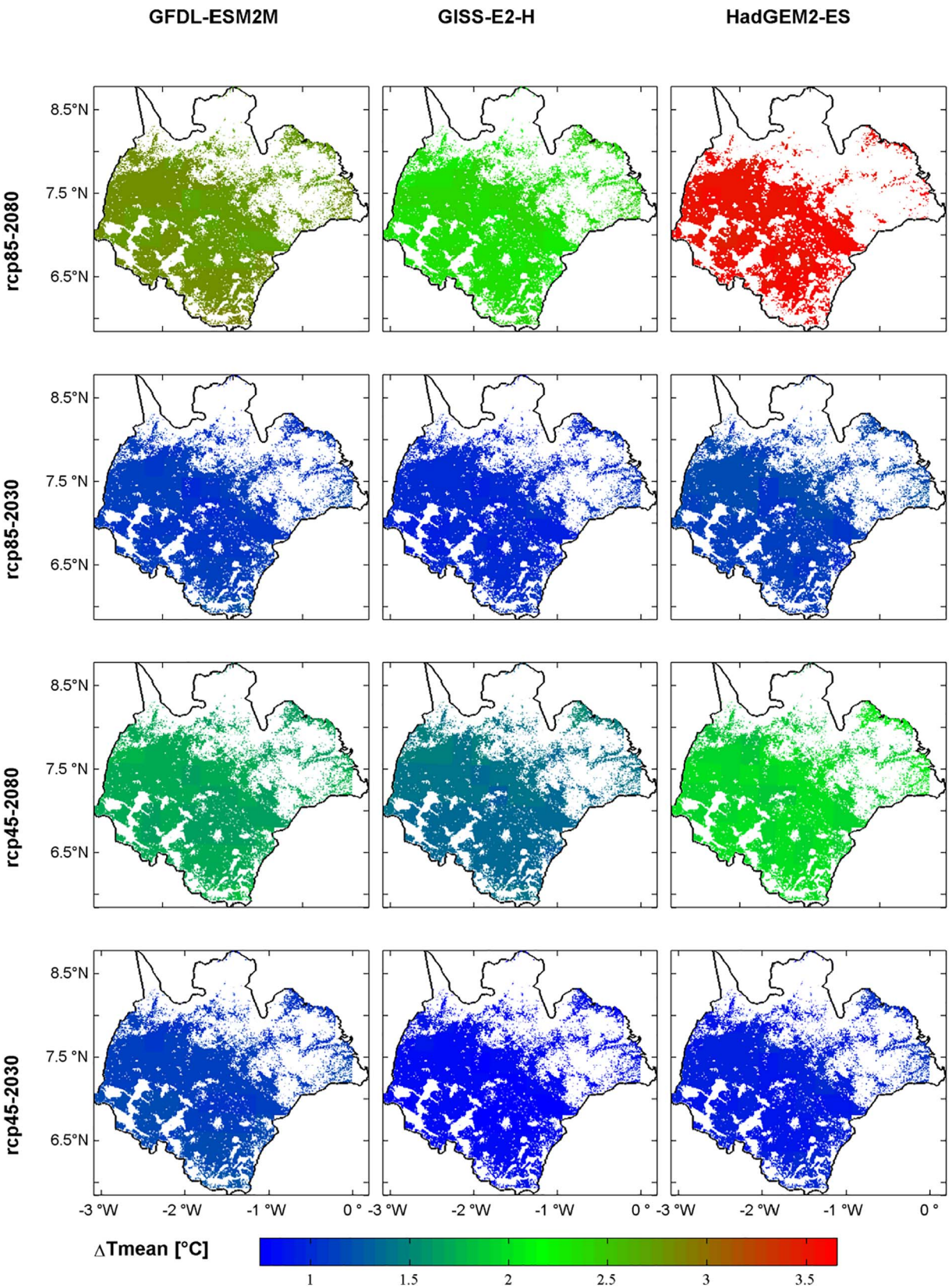

Fig. 3. Change in average mean temperature (Tmean) during the crop growth period for the RCP 4.5 and RCP 8.5 scenarios (2030–2000; 2080–2000) under the GCMs GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES compared to the baseline at columns 1, 2 and 3 respectively.

Table 4
Percentage change in precipitation, mean temperature (Mean Temp.), solar radiation, yield and above ground biomass (AGBiomass) values under all GCMs and RCPs for the time horizon 2030 and 2080 compared to the baseline values. Minimum (Min.) and Maximum (Max.) value show the variability in the study region.

GCMs and RCPs	Precipitation		Mean Temp.		Radiation		Yield		AGBiomass	
	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
GFDL-ESM2M_RCP45_2030	− 2.0	6.6	4.2	3.5	− 7.6	− 6.9	61.3	8.8	63.2	9.7
GFDL-ESM2M_RCP45_2080	− 0.5	− 0.7	6.5	5.3	− 8.8	− 8.9	58.5	12.2	60.1	12.8
GFDL-ESM2M_RCP85_2030	− 6.2	5.8	4.2	3.2	− 7.2	− 6.1	61.0	17.2	62.2	18.8
GFDL-ESM2M_RCP85_2080	− 5.5	4.7	10.6	9.2	− 13.7	− 14.4	59.4	3.6	59.7	2.9
GISS-E2-H_RCP45_2030	− 4.8	3.2	3.2	2.6	− 2.8	− 2.2	62.1	23.5	63.3	25.0
GISS-E2-H_RCP45_2080	− 16.0	− 0.6	5.4	4.7	− 4.3	− 3.9	62.1	25.9	62.4	27.2
GISS-E2-H_RCP85_2030	− 2.1	0.0	3.8	3.0	− 3.3	− 2.6	63.1	23.7	63.6	24.8
GISS-E2-H_RCP85_2080	− 15.7	− 2.2	9.1	7.6	− 6.7	− 6.6	65.5	27.5	65.1	27.5
HadGEM2-ES_RCP45_2030	− 8.8	− 9.3	3.7	2.8	− 3.4	− 3.3	60.6	29.5	61.7	31.7
HadGEM2-ES_RCP45_2080	− 32.1	− 27.4	7.5	6.0	− 5.3	− 4.8	65.6	27.7	66.7	29.1
HadGEM2-ES_RCP85_2030	− 5.9	− 23.8	4.4	3.7	− 2.0	− 2.5	65.6	34.6	66.6	36.7
HadGEM2-ES_RCP85_2080	− 27.9	− 17.8	13.4	11.7	− 10.7	− 11.1	64.8	9.7	65.0	9.5

because of stiff competition with weeds that set up after the first rains (Laux et al., 2008). The effect of elevated CO2 on radiation use efficiency has been taken into account. However, no separate impact of changes in meteorological variables on crop yield without considering the respective elevated CO_2 concentration was analysed in the future scenarios in order to avoid an additional source of uncertainty in crop yield projections which has been argued extensively especially in Africa (Soussana et al., 2010; Roudier et al., 2011).

The long season maize cultivar was selected by hypothesizing that about 85% of maize is grown during the major rainy season from April to September (Folberth et al., 2012; USDA PECAD, 2004).The field experiments were conducted under rainfed conditions with different levels of NPK application. The maize crop parameter dataset provided with the WOFOST model (Ceglar et al., 2011; Boons-Prins et al., 1993), was used as a starting point to establish a new parameter set for the maize variety Obatanpa. The parameters were adjusted so that simulated results for phenology, LAI, biomass, and yield could match observations from the field experiment (see calibration details in Srivastava et al., 2016; and Table 3). As a measure of accuracy (Table 3), to compare the observed data and simulated values, the following objective function was used (Papula, 1982):

a. The mean relative error MR as:

$$MR = \frac{1}{n}\sum_{i=1}^{n}\frac{(y_i - x_i)}{x_i}$$

b. The mean residual error ME as:

$$ME = \frac{1}{n}\sum_{i=1}^{n} y_i - x_i$$

where n is the sample number, x is the observed and y is the simulated value. A value of 0 of mean residual error (ME) indicates no systematic bias between simulated and measured values. The mean relative error (MR) gives an indication of the mean magnitude of the error in relation to the observed value. Small values indicate little difference between simulated and measured values.

3. Results

3.1. Model calibration and evaluation

The model solution SIMPLACE < Lintul5, Slim > was calibrated for the maize variety Obatanpa (a long cycle variety) on two contrasting soil types, under fertilized and unfertilized conditions during the year 2011. The observed and simulated day of anthesis and day of maturity under fertilized and control (unfertilized) treatments agreed well with an exception in Cheshegu, where the model underestimated the day of maturity by 8 days under both fertilized and control treatments (Table 3). The mean of simulated aboveground biomass agreed very well under fertilized treatments in both the sites whereas, in unfertilized treatments, the model underestimated the simulated biomass by 2% and 25% in Cheshegu and Akukayili respectively. The simulated yield was overestimated by about 20% under fertilized condition, whereas, the model did not capture the grain yield level under control condition as observed grain yield was extremely low.

3.2. Future climate characteristics relative to baseline

Figs. 2 and 3 respectively describe the differences between the time-averaged cumulated precipitation and mean temperature for the three GCMs and the baseline, during the crop growth period in the 2030 and 2080 time slices. The three GCMs include GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES and the two RCPs (RCP 4.5, and RCP 8.5). Average annual precipitation changed considerably across the GCMs and across the scenarios; noticeably, the maximum reduction is observed in the cumulated precipitation (193.9 mm) compared to the baseline under HadGEM2-ES (RCP 4.5) for the time horizon 2080, centred over the western part of the region (Fig. 2), whereas, under GFDL-ESM2M, an increase in the cumulated precipitation amount (a maximum of 41.8 mm) was observed under RCP 4.5 by 2030 compared to the baseline, centred in the southern part of the region (Fig. 2). There is a large variability across the study region, in projections of precipitation, varying from a minimum of − 32.1% decrease with HadGEM2-ES (RCP 4.5-2080) to a maximum increase of 6.6% under GFDL-ESM2M (RCP 4.5) by time horizon 2030 (Table 4).

Fig. 3 shows a significant change in the projections of mean temperature during the crop growth season in the study region for the future scenarios. On an average, the projected mean temperature may increase in the range of 0.7 °C (GISS-E2-RCP 4.5-2030) to a maximum of 3.6 °C under HadGEM2-ES (RCP 8.5; 2080) compared to the baseline mean temperature values. The variability ranges from a minimum of 3.2% increase under GISS-E2-H (RCP 4.5) by time horizon 2030 to a maximum of 11.7% increase under HadGEM2-ES (RCP 8.5) by time horizon 2080, compared to the baseline mean temperature across the study region (Table 4). These projected changes in the mean temperature are also in line with the IPCC AR5 simulation for West Africa that predicted a rise in mean temperature of 4.6 °C by 2100 under RCP 8.5 (IPCC, 2014). Moreover, based on the projection by the World Bank (2010), the trend for temperature over the period 2010–2050 also indicates warming in all regions of Ghana but to a milder extent. For instance, based on the scenario, the predicted rise in the Ashanti region will be 1.7–2.0 °C and that of Brong-Ahafo region will be 1.3–1.6 °C between 2030 and 2060.

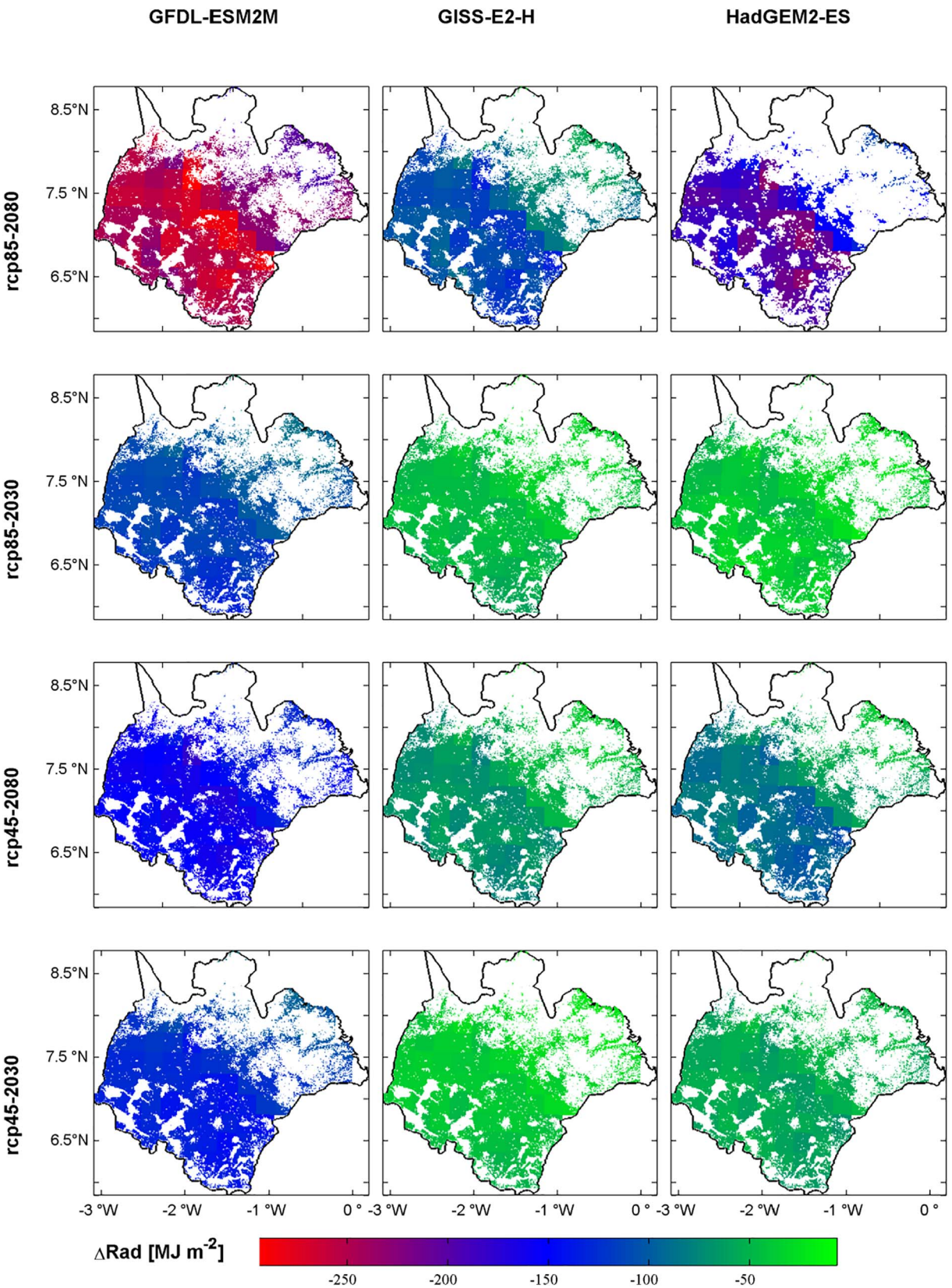

Fig. 4. Change in average solar radiation (Rad) during the crop growth period for the RCP 4.5 and RCP 8.5 scenarios (2030–2000; 2080–2000) under the GCMs GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES compared to the baseline at columns 1, 2 and 3 respectively.

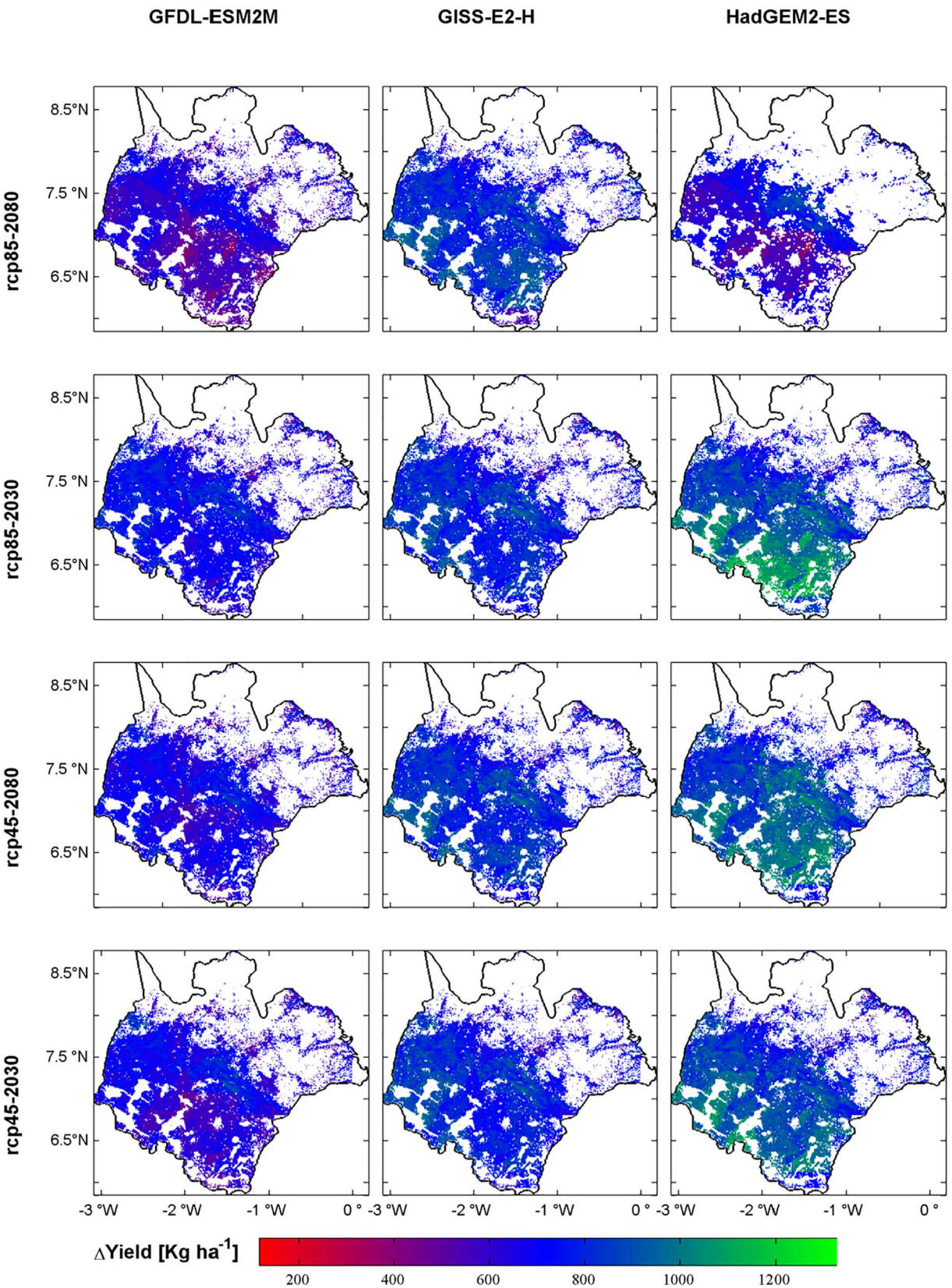

Fig. 5. Absolute change in mean simulated maize yield for the RCP 4.5 and RCP 8.5 scenarios (2030–2000; 2080–2000) under the GCMs GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES compared to the baseline at columns 1, 2 and 3 respectively.

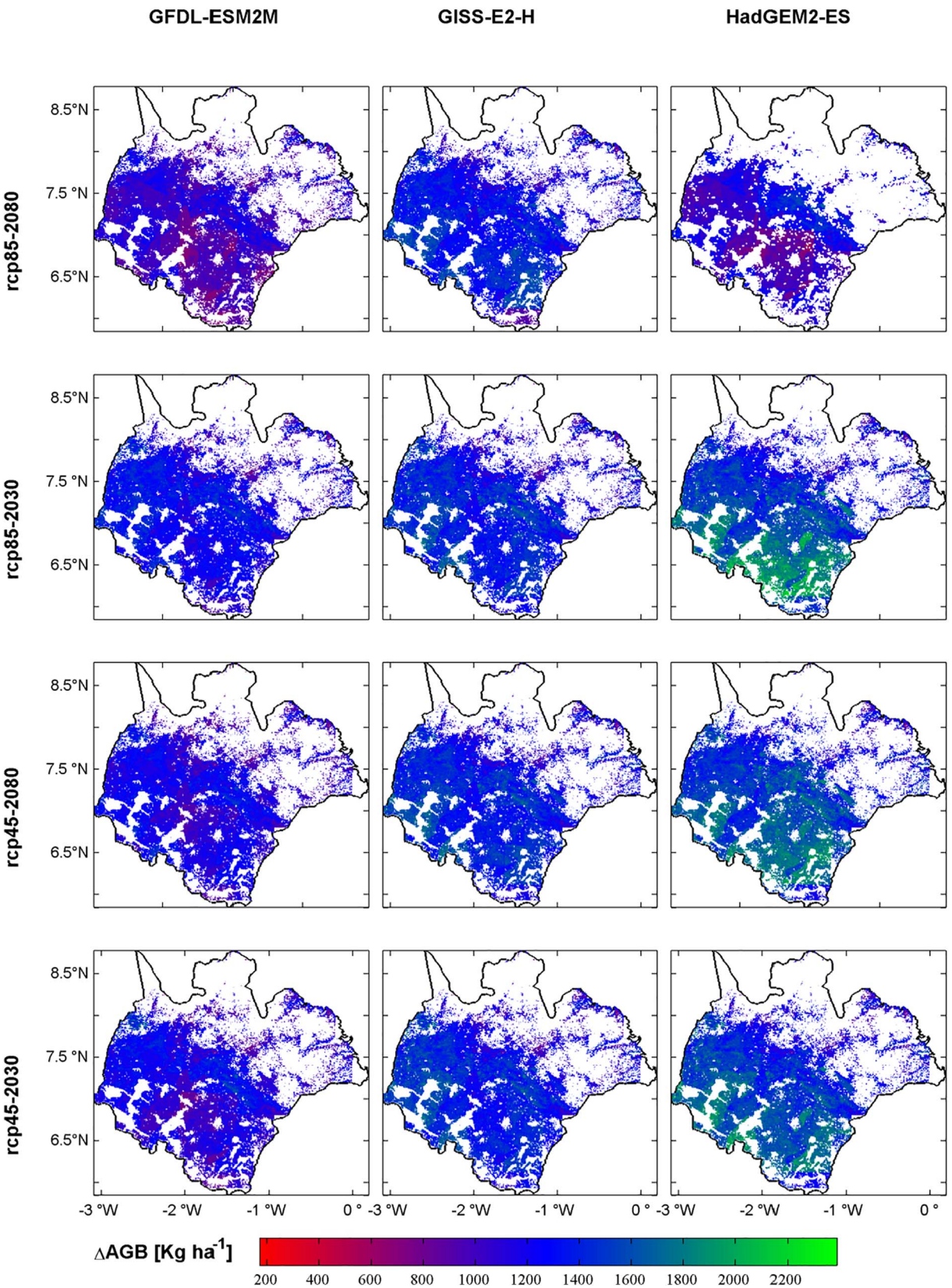

Fig. 6. Absolute change in simulated maize aboveground biomass (AGB) for the RCP 4.5 and RCP 8.5 scenarios (2030–2000; 2080–2000) under the GCMs GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES compared to the baseline at columns 1, 2 and 3 respectively.

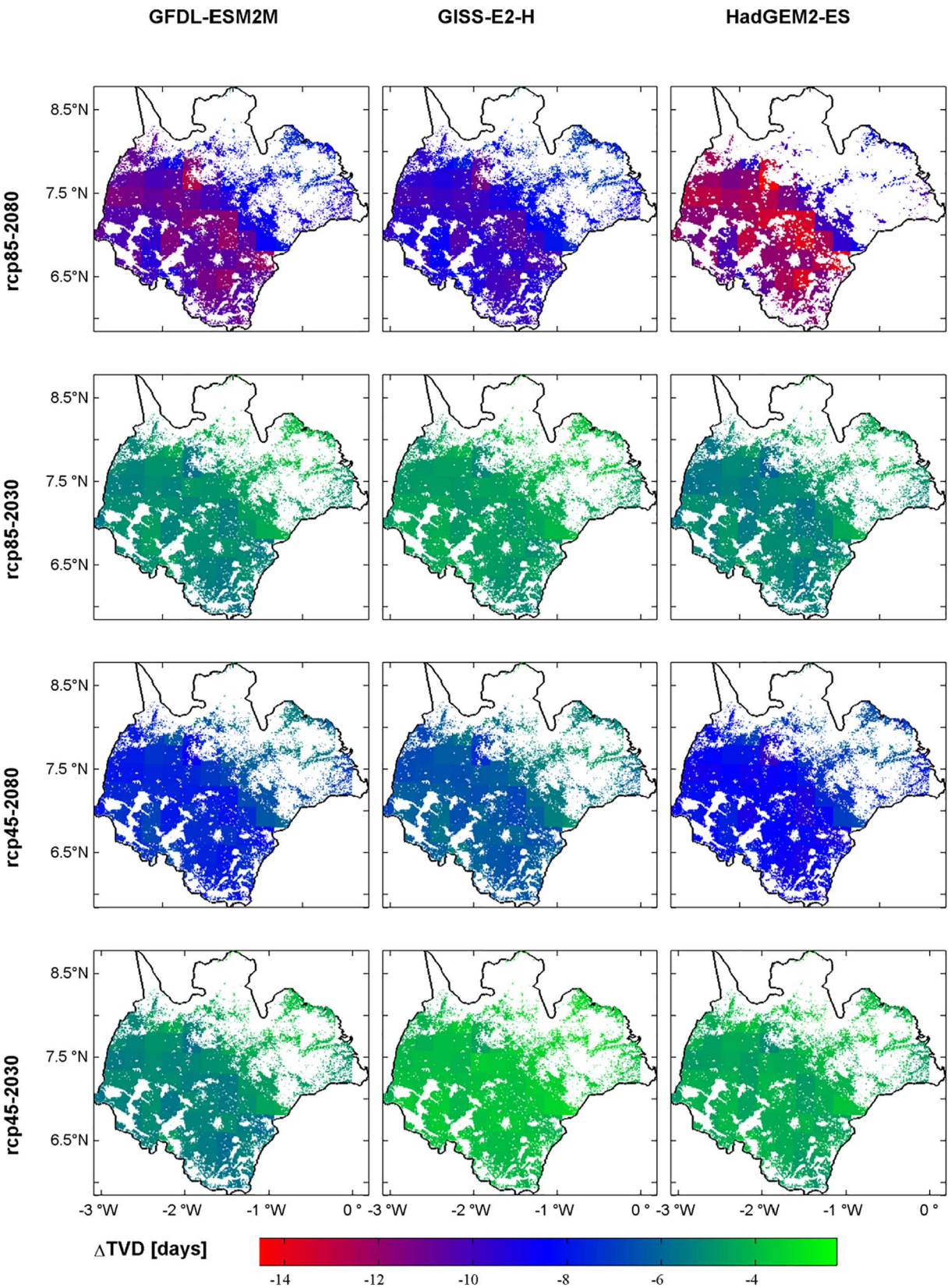

Fig. 7. Change in Total vegetation days (TVD) for scenarios (RCP 4.5 and RCP 8.5, 2030–2000; 2080–2000) under the GCMs (GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES) compared to the baseline at columns 1, 2 and 3 respectively.

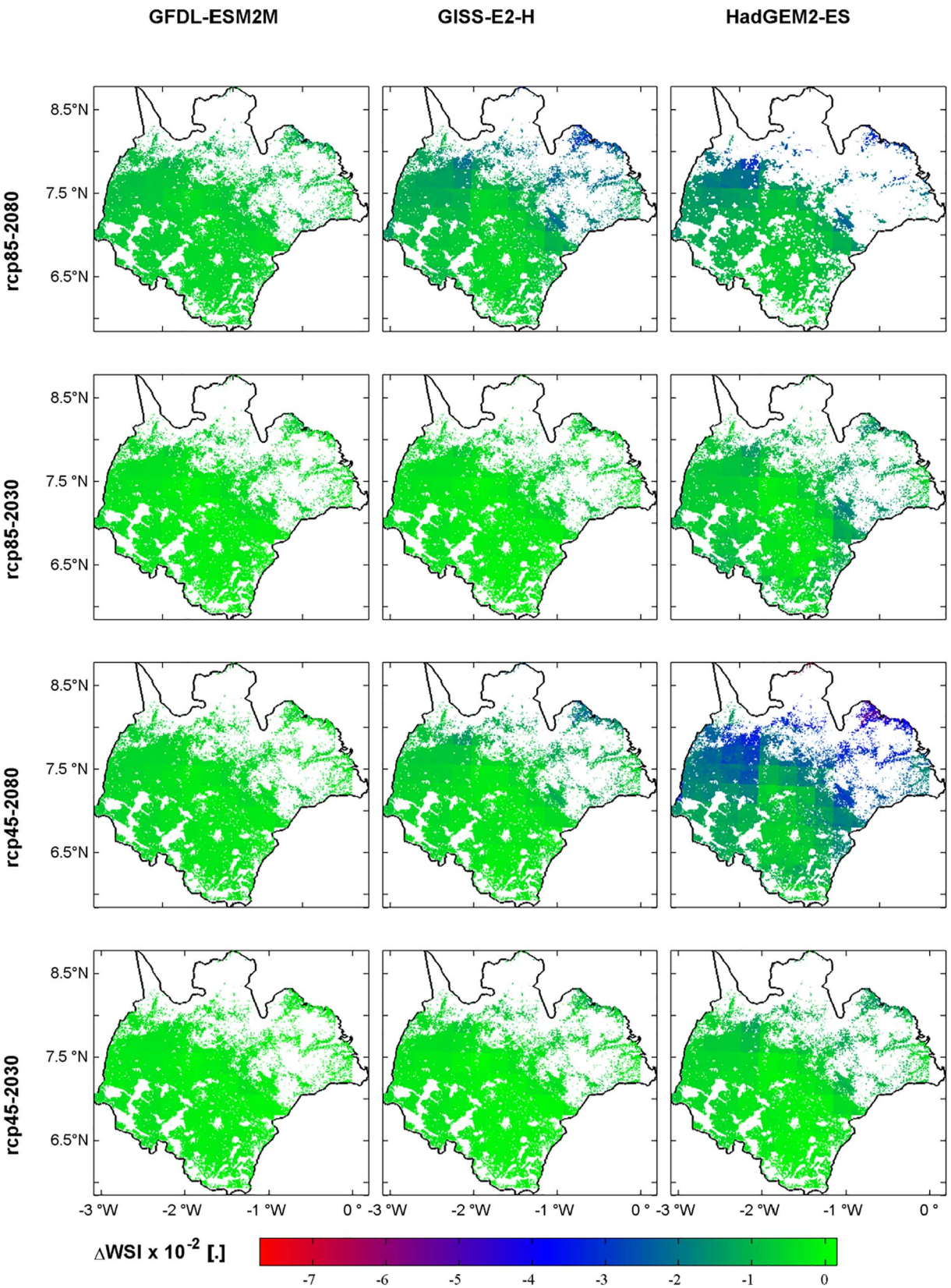

Fig. 8. Change in Water Stress Index (WSI) in the crop growth period for scenarios (RCP 4.5 and RCP 8.5, 2030–2000; 2080–2000) under the GCMs (GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES) compared to the baseline at columns 1, 2 and 3 respectively.

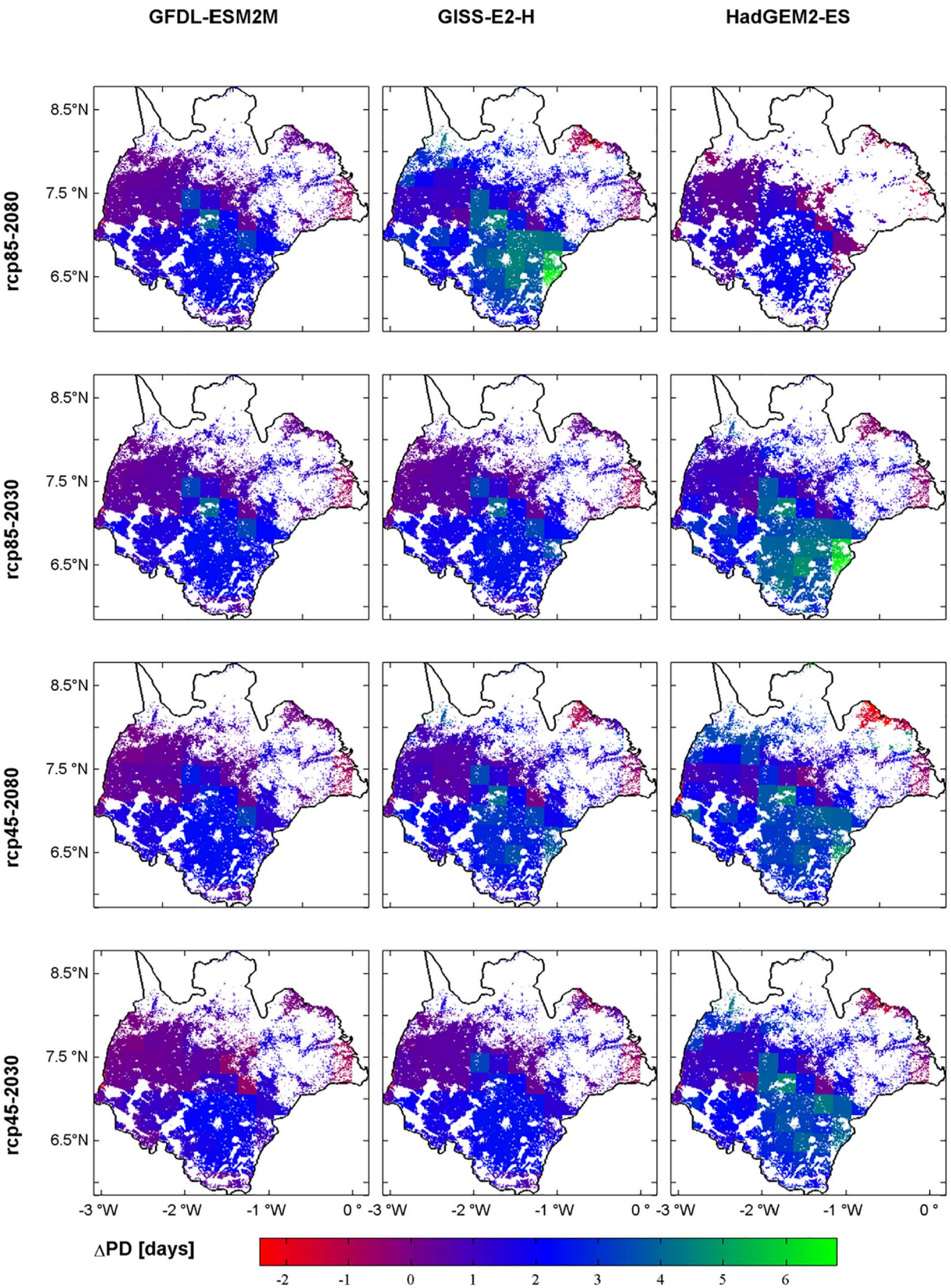

Fig. 9. Change in planting date (PD) for scenarios (RCP 4.5 and RCP 8.5, 2030–2000; 2080–2000) compared to the baseline under the GCMs (GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES) at columns 1, 2 and 3 respectively.

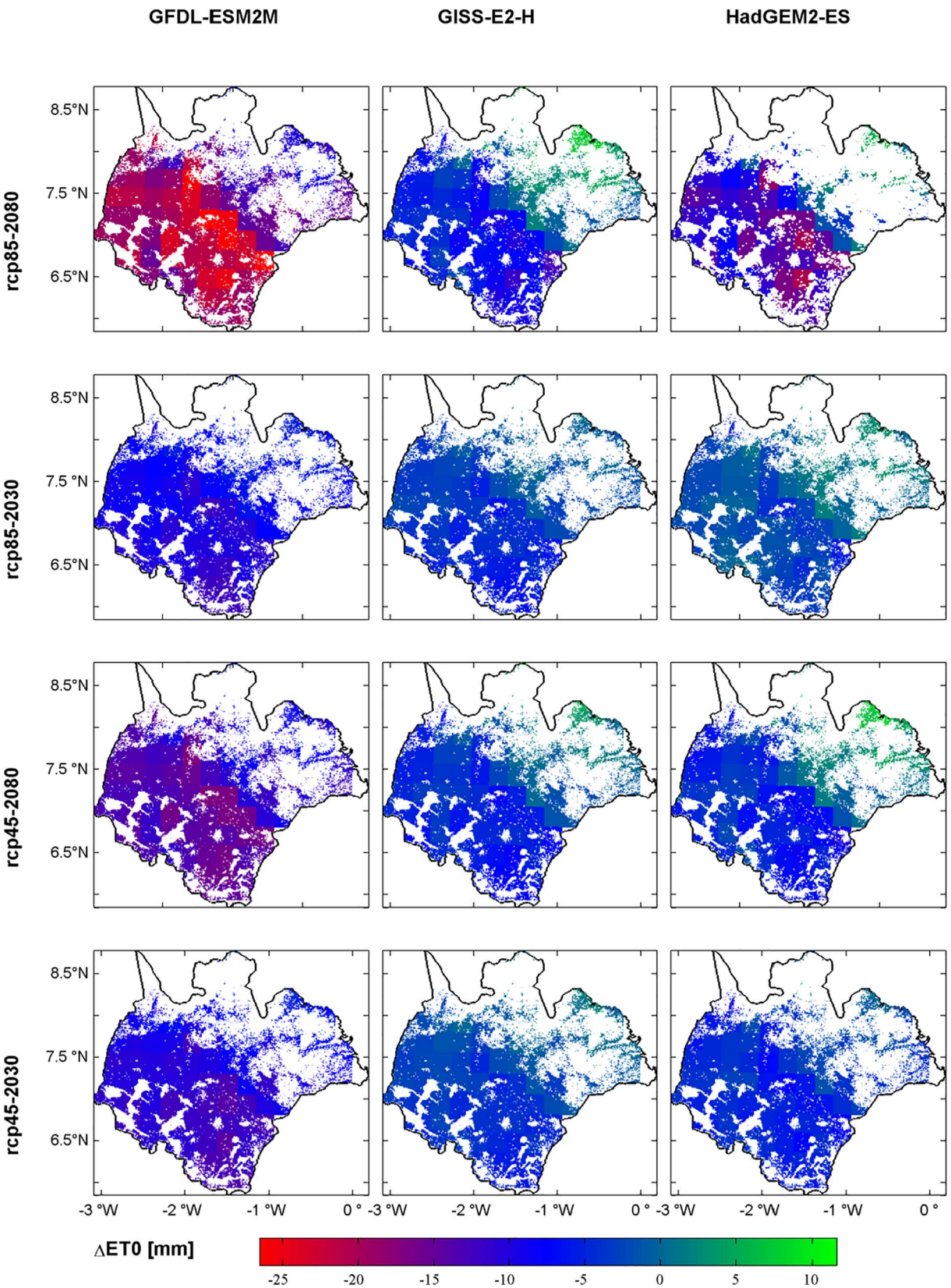

Fig. 10. Change in crop reference evapotranspiration (ET0) in the crop growth period for scenarios (RCP 4.5 and RCP 8.5, 2030–2000; 2080–2000) compared to the baseline under the GCMs (GFDL-ESM2M, GISS-E2-H, and HadGEM2-ES) at columns 1, 2 and 3 respectively.

Regarding cumulated radiation (Fig. 4) in the crop growth period, an average reduction of 248.9 MJ m^{-2} was projected under GFDL-ESM2M (RCP 8.5) by time horizon 2080 compared to the baseline cumulated radiation values. Whereas, overall variability across the study region ranges from −2.0% to −14.4% decrease under HadGEM2-ES (RCP 8.5) by time horizon 2030 and GFDL-ESM2M (RCP 8.5) by time horizon 2080 respectively (Table 4). The length of crop growth cycle (i.e., total vegetation days) was shortened in the projected climate scenarios compared to the baseline period varying from −4 days to a maximum of −14 days under HadGEM2-ES (RCP 8.5) by the time horizon 2080 across the study region (Fig. 7), whereas, onset of simulated planting date shifted, varying from +6 days to −2 days (Fig. 9) across the study region compared to the baseline period. The reference evapotranspiration varied from +10 mm to −25 mm compared to the beseline period (Fig. 10). Maximum reduction of −25 mm was simulated under GFDL-ESM2M (RCP 8.5) by time horizon 2080. Regarding water stress index, except for few patches under HadGEM2-ES and GISS-E2-H, there was almost no change in water stress for the crop during the growing season (Fig. 8).

3.3. Impact on maize yield and aboveground biomass under climate change scenarios

The overall expected situation of maize yield and aboveground biomass is not different across the GCMs and RCPs for the time horizons 2030 and 2080. There is a consistent increase in the projected average maize yield compared to the baseline yields, ranging from 183.6 kg ha^{-1} under HadGEM2-ES (RCP 8.5) by time horizon 2080 to a maximum of 1326.8 kg ha^{-1} under HadGEM2-ES (RCP 8.5) by 2030 (Fig. 5). Likewise, aboveground biomass also increased in the future scenarios (Fig. 6) with an average value of 1544.6 kg ha^{-1} under HadGEM2-ES (RCP 8.5) by time horizon 2030 compared to the baseline. The variability in aboveground biomass increase across the study region ranges from a minimum of 169.9 kg ha^{-1} under GFDL-ESM2M (RCP 8.5) by time horizon 2080 to a maximum increase of 2386.1 kg ha^{-1} under HadGEM2-ES (RCP 8.5) by time horizon 2030.

4. Discussion

In general, there is a trend of increasing maize yields under all climate scenarios produced by the three GCMs. This increase in maize yields in the future climate scenarios may be due to increase in CO_2 concentration in the atmosphere (Table 1a) combined with only moderate to no changes in the amount of precipitation and incoming radiation during the growing cycle of maize. Elevated CO_2 concentration in the atmosphere has the potential to increase the crop water productivity by enhancing photosynthesis and reducing leaf-level transpiration of plants (Deryng et al., 2016), although in our simulation only the CO_2 effect on net photosynthesis has been considered. Recently, Delusca et al. (2016) have also reported a 40% increase in maize yield under 550 ppm CO_2 compared to the ambient 387 ppm CO_2 concentration. Significant increase in crop yield due to elevated levels of CO_2 has been reported in experiments by Deryng et al. (2016) and Kimball et al. (2002). According to Berg et al. (2013), C4 crops benefitted from elevated CO_2 in arid regions through increased water use efficiency. However, there is an ongoing debate about the extent of CO_2 fertilization impacts on crop yield especially in Africa (Sultan and Gaetani, 2016) where there is lack of observations for model validation and improvements as there are no free air carbon dioxide enrichment (FACE) experiments in Africa (Roudier et al., 2011).

The differences in spatial patterns of yield changes (Fig. 5) correlate with the increased mean temperature (Fig. 3) and reduced radiation (Fig. 4) in the growing season of maize. Warmer climates would generally accelerate the growth and development of plants; earlier flowering and maturity of several crops have been documented in recent decades to be often associated with higher temperatures (Craufurd and Wheeler, 2009). The reason for the lower increase in yields in the GFDL-ESM scenarios could be attributed to the strongest reduction of incoming radiation compared to the other two GCMs (GISS-E2-H, and HadGEM2-ES). In all the climate scenarios, radiation has declined up to a maximum of 14.4% (Table 4) compared to the baseline radiation values, which may reduce the atmospheric water demand (refer Fig. 10), resulting in less water stress to the plants (Fig. 8) and leading to improved yields. The same has been reported by Estes et al. (2014) where he argued that declining net radiation reduced atmospheric water demand almost uniformly across the West African countries. Changes in temperature and rainfall amounts will combine to bring about shifts in the onset and length of growing seasons in the future. Adiku et al. (2015) also reported an increase in maize yield by 12% under the influence of future climate in Navrongo, situated in the northern part of Ghana.

More recently, Deryng (2015) also noted that simulated mean yield of rain-fed maize increased by 5 ± 6.8% in semi-arid areas in West Africa by 2030 under RCP 8.5.

Projected changes in the length of the growing period for Africa to the 2090s were estimated by Thornton et al. (2011) for an ensemble of 14 GCMs. A large proportion of the cropping and rangeland area of sub-Saharan Africa was projected to see a decrease in growing season length, and most of Africa in the southern latitudes may see losses of at least 20%. In the present analysis, the negative effect of shortened growing cycle (Fig. 7) on maize yield may have been counterbalanced by the increased radiation use efficiency under elevated CO_2 concentrations. In addition, the maize yield may have benefitted from a variable onset of planting in the future climate scenarios because of a rainfall-driven rule based planting method (described in Section 2.4). This rule based planting method can be considered as an autonomous adaptation measure which farmers may carry out to tackle the impact of future climate change. In regions with pronounced rainy and dry seasons, sowing generally occurs around the start of the rainy season (Srivastava et al., 2016). In particular, maize is usually planted when monthly average precipitation reaches 80–140 mm $month^{-1}$ (Sacks et al., 2010). However, there is considerable spread in these relationships between sowing date and precipitation depending on the location and on the annual rainfall distribution, which, therefore, delineate the difference between regions and hence suggests, using precipitation driven rule-based approaches for estimating sowing dates at a regional scale (Srivastava et al., 2016). In the current study, the planting date shifted by 1–5 days mainly in the South-Eastern part of the study region, up to a maximum of 7 days under HadGEM2-ES (RCP 8.5) by the time horizon 2030 and under GISS-E2-H (RCP 8.5) by the time horizon 2080 (Fig. 9). In terms of timing of growing season onset, Crespo et al. (2011) also demonstrated that it may be possible to adapt to projected climate shifts to at least the 2050s in maize production systems in parts of southern Africa by changing planting dates.

Despite the uncertainty surrounding the absolute changes, climate variability and its impact on the temporal variability of maize yields needs to be taken into account. For example, the impacts of climate change to the middle of this century on maize yields in parts of East Africa may be underestimated by 3.6%, if only changes in climatic means are taken into account and climate variability and its impact on yield variability is ignored (Rowhani et al., 2011).

The strong positive effect of high CO_2 on simulated crop yields constitute a source of uncertainty across GCM projections due to the uncertainty associated with the question how well stimulated photosynthesis can actually be translated into higher yields especially in C4 crops like maize. Some caution must also be attached to our findings since, among the assumptions made in the simulation study, model calibration was carried out based on one dominant maize variety only, making reference data for the whole target region. Hence, this study can be refined by interacting with local experts, farmers so that other local varieties of maize can be identified which farmers use to cultivate. Other aspects that could affect agricultural production in this region in

the future are not considered in these simulations, such as direct heat stress (Müller et al., 2015; Siebert et al., 2014). However, the threshold of 36 °C during the maize growing period is rarely reached in our study regions even in the hottest climate scenario (HadGEM2-ES, RCP 8.5) in the time slice 2080 investigated here. Other factors which could be included are ozone damage (Pleijel and Uddling, 2012); and altered pressure from weeds, pests, and diseases (Hatfield et al., 2011). Also, production systems were abstracted at the level of the crop. If cropping systems were analysed instead, crop performance in a given cell would result from its performance in different rotations and under different inputs of resources.

5. Conclusions

There is a substantial increase in the average maize yield in all projected future climate scenarios analysed compared to the baseline due to the beneficial effect of CO_2 on the radiation use efficiency of the crop combined with only moderate changes in amount of rainfall and incoming radiation during the growing cycle of maize. Secondly, across all climate scenarios, it is evident in this region that today and under future clime conditions water would not be the most limiting factor during the maize growth period, whereas, temperature (through shortening of the maize growing cycle), nutrients and solar radiation may remain the limiting factor for maize production in the region.

However, further studies should include spatial distribution and their expected changes over time of different cropping systems (e.g., rotations or intercropping with root or tuber crops) and consider, variable fertilizer application rates within the area.

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